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Intelligent Multi Criteria Decision Making Methods for Material Selection in Sugar Industry

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Abstract

The best material selection for a given application involves numbers of criteria of conflicting nature to be considered. Material that has the properties that provide the necessary service performance must be selected from the range of suitable alternative materials for manufacturing of structural parts. A poorly chosen material can add to manufacturing cost and unnecessarily increase the cost of the part. Also, the properties of the part may be changed by processing, and that may affect the service performance of the part. These conditions lead to introduce some intelligent, systematic as well as logical method to choose best alternative material for the end product. The purpose of this paper is to disclose the application of four intelligent Multi Criteria Decision Making methods for solving material selection of pipes in sugar industry. Extended TODIM, ARAS, OCRA, EVAMIX are the methods used for the best material selection from five alternative materials.

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Keywords: Selection of materials; influence of criteria; Extended TODIM, EVAMIX, OCRA, ARAS

1. Introduction

Material selection is an important activity in the design of an effective manufacturing and performance of end product. Selecting appropriate material can decrease manufacturing time, increase the efficiency of process and increase productivity. Material selection plays an important role in the manufacturing of structural element. Determination of proper material is difficult tasks because of the material for selection is having a range of distinct characteristics and cost that distinguish from others.

Wear and corrosion are the most important factors that the surface of the engineering parts like pipes used in sugar industry must confront. The need for protection and improvement of the mechanical characteristics of the structural parts can be to some extent satisfied by making a proper decision. For selecting the most suitable material in the sensitive structural element like pipes, the selection from complex comparison among candidate materials and for each material selection criterion, a wide range of material properties and performance indices should be taken in

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account involving wear and corrosion behavior of the material. Moreover, in order to explore better design alternatives, it is always vital to gain rapid knowledge of new materials under development (Shanian and Savadogo, 2009). Thus, the material selection process can be efficient enough in order to select the best alternative for a given engineering application.

2. Review on literature for material selection

The material selection should not be solely based on any single criterion. A systematic approach to material selection process is necessary in order to select the best material for the given application. The proper material selection technique involves carefully defining the application requirement in terms of mechanical properties mainly for type of utility described in the proposed application.

Edwards (2005) put forward an approach for material selection for optimum use in engineering components. Deng and Edwards (2007) put forward a data modeling in a chart format for material selection. Dweiri and Al-Oqla (2006) proposed Analytical hierarchy process, technique or order preference by similarity to ideal solution (TOPSIS) method by (Maitya and Chakraborty, 2013; Rathod and Kanzaria, 2011; Rao and Devim, 2008; Shanian and Savadogo, 2006;Milani et al., 2005; Jee and Kang, 2000), graph theory and matrix approach (Rao, 2008), Elimination and choice expressing the reality (ELECTRE) method (Shanian and Savadogo, 2006a; 2006b; Chatterjee et al., 2009), Vlse Kriterijumska Optimizaciji Kompromisno Resenje (VIKOR) method (Chaterjee and Athawale, 2009; Rao 2008; Jahan et al., 2011), evaluation of mixed data (EVAMIX) method (Chaterjee et al., 2011; Darji and Rao, 2013), complex proportional assessment (COPRAS) method (Chaterjee et al., 2011), Chan (2006) proposed gray retioanl analysis, Chan and Tong (2007), a novel type preference selection index method (Maniya and Bhatt, 2010), Zhao et al. (2012) proposed environmental and economic evaluation of materials using grey relational analysis, multi-optimization on the basis of ratio analysis (MOORA) method (Karande and Chakraborty, 2012), TOPSIS and objective weighting material selection by (Jahan et al., 2012), Rao and Patel (2010) proposed a novel MADM method for material selection using fuzzy logic, Caliskan et. al., (2013) proposed a combination of various multi-criteria decision making methods for the tool holder material selection.

The review to the literature finds still efforts to be extended to identify some more effective and logical methods for the material selection problems.

2.1Material selection for sugar industry equipments

The material selection methodologies for sugar industry are reviewed in this section. Manshadi et al., (2007) have proposed Weighting Factor Method and studied the effect of austenitic stainless steel welded carbon steel roll. The main wear mechanism silica is ploughing and cutting the sugar cane roller shell (Casanova and Aguilar, 2008). Zumelzu et al. (2003) made an attempt to find the sugar cane roller shell (Casanova & Aguilar, 2008). Zumelzu et al. (2003) made an attempt to find out the characteristics and corrosion behavior of high-Cr White Iron. Buchanan, Shipway, and McCartney (2010) conducted two abrasion–corrosion tests such as Fe–Cr–C shielded metal arc welding (SMAW) hard facings used in the sugar industry and an arc sprayed Fe–Cr-based coating and concluded the abrasion–corrosion of SMAW high Fe–Cr–C coatings performance is lower compared to electric arc sprayed Fe–Cr based coating in slurry of sand and sugarcane juice. Panigrahi, Srikanth, and Singh (2007) examined the pitting corrosion in evaporator vessel using mild steel. Montakarntiwong, Chusilp, Tangchirapat, and Jaturapitakkul (2013) have investigated the thermal power plant concretes strength and heat conduction. Mariajaya prakash and Senthilvelan (2013) have applied Failure Mode Effective Analysis (FMEA) and Taguchi method for finding the failures of fuel feeding system. Hanamane, Attar, and Mudholkar (2013) developed the embedded fuzzy logic module for cogeneration system to improve the steam generation performance and saving fuel of boiler.

Anojkumar et al. (2014) proposed four multicriteria decision making methods: FAHP-TOPSIS, FAHP-VIKOR, FAHP-ELECTRE, FAHP-PROMTHEE for pipe material selection.

The aforementioned literature shows the importance of various MCDM methods in the material selection process. The suitable material for sugar industry equipment is also one among them. The existing research in sugar industry have proposed and used the various materials but the failures are not eradicated completely due to acidic nature of sugar cane juice. This paper focused on the application of intelligent MCDM methods for selection of suitable material for pipes.

3. Intelligent multi criteria decision making methods

In the proposed approach weights and criteria are adopted from (Anojkumat et. al. 2014) for the comparison of results and ranking obtained though these intelligent decision making methods. The ranking is carried out by using four methods known as: Extended TODIM, Operational Competitiveness Rating Analysis (OCRA), Additive Ratio Assessment (ARAS) method, and Evaluation of mixed data (EVAMIX) method.

3.1A numerical example: Material selection for pipe in sugar industry

The sugar industry is characterized by high maintenance costs due to the replacement and repair of equipment due to corrosion and corrosion abrasion. Sugar cane is not washed prior to cutting and crushing in the mills and the presence of sand and stone contribute to the abrasive conditions that already exist. Corrosion and rapid wear of industry equipment are widely recognized as major production-cost and quality problems in the sugar industry.

The short life of equipment and the need for excessively frequent cleaning and maintenance often involving disruption of crop processing, can make producing sugar an excessively expensive exercise. Even the quality of the sugar is affected. In the present paper attempts are made to suggest some economically efficient material from available group of materials. The materials are J4, JSLAUS, 204Cu, 409M and 304. The criteria under consideration of the best material selection are: Yield strength (YS), Ultimate tensile strength (UTS), % of elongation (% E), Hardness (H), Cost (C), Corrosion rate (CR) and Wear rate (WR). The data are tabulated in Table 1.

Table 1. Material properties for pipe lines (Anojkumat et. al. 2014).

Materials	Properties						
	YS	UTS	% E	H	C	CR	WR
J4	382	728	48	98	112	0.16	2.75
JSLAUS	420	790	58	97	210	0.31	2.63
204Cu	415	795	55	96	120	0.05	2.5
409 M	270	455	32	78	184	0.4	4
304	256	610	60	86	89	0.01	2.59
Weights	0.0602	0.0272	0.0369	0.0938	0.3480	0.2492	0.1846

Out of these seven criteria YS, UTS and H are the beneficial type and % E, C, CR and WR are the cost or non-beneficial type criteria.

3.2 Extended TODIM method

The basic idea of the TODIM method (an acronym in Portuguese of Interactive and Multicriteria Decision Making), is a discrete multi attribute method based on Prospect Theory is to measure the dominance degree of each alternative over the others by establishing a multi-attribute value function based on Prospect Theory. An extended TODIM method is developed to solve the MADM problem, where attribute values are represented in three formats: crisp number, interval numbers and fuzzy numbers (Fan et al., 2013).

Step 1: Transformation of data format of attributes values

The transformation process and calculation formula of crisp format is done using Eq. (1). If γ_{ij} is a crisp number, i.e., $x_{ij} = x'_{ij}$, it can be regarded as particular random variable.

$$F_{ij}(x) = \begin{cases} 0, & x < x'_{ij}, \\ 1, & x \geq x'_{ij}, \end{cases} \quad i \in M, \quad j \in N^k \tag{1}$$

Step 2: Construct gain matrices and loss matrices.

Let x_{ij} and x_{kj} be the attribute value of alternatives A_i and A_k concerning attributes C_j, respectively, $i, k \in M, j \in N$. Let $F_{ij}(x)$ and $F_{kj}(x)$ be the cumulative distribution functions of x_{ij} and x_{kj}, respectively. For the benefit attributes, the superior and inferior values of $F_{ij}(x)$ relative to $F_{kj}(x)$ are respectively expressed by

For sets Ω_{ik}^{j} and Θ_{ik}^{j} , the gain of alternative A_i relative to alternative A_k concerning attribute C_j , G_{ik}^{j} , is expressed by

$$G_{ik}^{j} = D(F_{ij}(x), F_{kj}(x)) \qquad i,k \in M, \quad j \in N. \qquad G_{ik}^{j} \geq 0 \tag{2}$$

Correspondingly, the loss of A_i relative to A_k , L_{ik}^{j} is expressed by

$$L_{ik}^{j} = -T(F_{ij}(x), F_{kj}(x)) \qquad i,k \in M, \quad j \in N. \qquad L_{ik}^{j} \leq 0 \tag{3}$$

Based on the above analysis, gain matrix $G_j = \left[G_{ik}^{j}\right]_{mxm}$ and loss matrix $L_j = \left[L_{ik}^{j}\right]_{mxm}$ concerning attributes C_j can be constructed.

Step 3: Construct normalized matrices for gain and loss matrices.

The normalized matrix of every element in matrix $G_j = \left[G_{ik}^{j}\right]_{mxm}$ or $L_j = \left[L_{ik}^{j}\right]_{mxm}$ is formulated i.e., matrix $Y_j = \left[Y_{ik}^{j}\right]_{mxm}$ or $Z_j = \left[Z_{ik}^{j}\right]_{mxm}$.

$$Y_{ik}^{j} = \frac{G_{ik}^{j} - G_{j}^{min}}{G_{j}^{max} - G_{j}^{min}}, \qquad i,k \in M, \quad j \in N \quad , Y_{ik}^{j} \in [0,1] \tag{4}$$

$$Z_{ik}^{j} = \frac{L_{ik}^{j} - L_{j}^{max}}{L_{j}^{max} - L_{j}^{min}}, \qquad i,k \in M, \quad j \in N \quad , Z_{ik}^{j} \in [-1,0] \tag{5}$$

Step 4: Construct dominance degree matrix.

The dominance degree for the gain $\Phi_{ik}^{j(+)}$ is given by Fan et. al. (2013) as follow:

$$\Phi_{ik}^{j(+)} = \sqrt{\frac{w_j Y_{ik}^{j}}{w_r \sum_{j=1}^{n}(w_j/w_r)}}, \qquad i,k \in M, \quad j \in N \qquad , 0 \leq \Phi_{ik}^{j(+)} < 1 \tag{6}$$

And the dominance degree for the loss, $\Phi_{ik}^{j(-)}$, is given by

$$\Phi_{ik}^{j(-)} = \frac{-1}{\theta}\sqrt{\frac{-Z_{ik}^{j} w_r}{w_j}\sum_{j=1}^{n}(w_j/w_r)}, \qquad i,k \in M, \quad j \in N \qquad , \Phi_{ik}^{j(-)} \leq 0 \tag{7}$$

Where $w_r = \max\left\{w_j \mid j \in N\right\}$, and θ is the attenuation factor of the loss. θ denotes the degree of loss aversion i.e., $\theta > 0$. The greater θ is, the lower the degree of loss aversion is. Further, dominance degrees $\Phi_{ik}^{j(+)}$ and $\Phi_{ik}^{j(-)}$ are aggregated, i.e., $\Phi_{ik}^{j} = \Phi_{ik}^{j(+)} + \Phi_{ik}^{j(-)}$, $\quad i,k \in M, \quad j \in N$ (8)

Step 5: Construct overall value of each alternative

Moreover, based on matrix Φ_j , the overall dominance degree matrix, Δ , is constructed, i.e., $\Delta = \left[\delta_{ik}\right]_{mxm}$, where δ_{ik} is the overall dominance degree of alternative A_i over alternative A_k , i.e.,

$$\delta_{ik} = \sum_{j=1}^{n} \Phi_{ik}^{j}, \qquad i.k \in M \tag{9}$$

Step 6: Calculate the overall value of each alternative based on matrix Δ. The overall value of alternative A_i, $\xi(A_i)$, can be calculated, i.e.,

$$\xi(A_i) = \frac{\sum_{k=1}^{m}\delta_{ik} - \min_{i\in M}\left\{\sum_{k=1}^{m}\delta_{ik}\right\}}{\max_{i\in M}\left\{\sum_{k=1}^{m}\delta_{ik}\right\} - \min_{i\in M}\left\{\sum_{k=1}^{m}\delta_{ik}\right\}}, \qquad i \in M \tag{10}$$

Step 7: Determine the ranking order of alternatives according to the obtained overall values. It is clear that,

$0 \le \xi(A_i) \le 1$, and the greater $\xi(A_i)$ is, the better alternative A_i will be.

3.3 OCRA method

The procedural steps of the current method are described by Chatterjee and Chakraborty (2012) are:

Step 1: Compute the preference ratings with respect to the non-beneficial attribute.

In this step, OCRA method is only concerned with the scores that various alternatives receive for the input attribute without considering the scores received for the beneficial attribute. The lower values of non-beneficial or input criteria are more preferable. The arrogate performance of i^{th} alternative with respect to all the input attribute is calculated using the following equation:

$$\bar{I}_i = \sum_{j=1}^{n} w_j \frac{\max(x_j^m) - x_i^j}{\min(x_j^m)} \qquad (i = 1,2,\ldots,m;\ j = 1,\ldots,n;\ i \ne m) \tag{11}$$

Where $\bar{I}_i$ is the measure of the relative performance of i^{th} alternative and x_j^i is the performance score of i^{th} alternative with respect to j^{th} input criterion. The calibration constant w_j (relative importance of j^{th} criterion) is used to increase or reduce the impact of this difference on the rating $\bar{I}_i$ with respect to j^{th} criterion.

Step 2: Calculate the linear preference rating for the input criteria. $\bar{\bar{I}}_i = \bar{I}_i - \min(\bar{I}_i)$ (12)

Step 3: Compute the preference ratings with respect to the beneficial criterion.

The aggregate performance for i^{th} alternative on all the beneficial or output criteria is measure using the following expression: $\bar{O}_i = \sum_{h=1}^{H} w_h \frac{x_h^j - \min(x_h^m)}{\min(x_h^m)}$ (13)

Where $h = 1,2,\ldots,H$ indicates the number of beneficial attributes or output attribute and w_h is calibration constant or weight importance of h^{th} output criteria. The higher an alternative's score for an output criterion, the higher is the preference for that alternative. It can be mentioned that $\sum_{j=1}^{n} w_j + \sum_{h=1}^{H} w_h = 1$.

Step 4: Calculate the linear preference rating for the output criteria: $\bar{\bar{O}}_i = \bar{O}_i - \min(\bar{O}_i)$ (14)

Step 5: Compute the overall preference ratings. For each alternative (P_i) is calculated by scaling the sum $(\bar{\bar{I}}_i + \bar{\bar{O}}_i)$ so that the least preferable alternative receives a rating of zero. $P_i = \left(\bar{\bar{I}}_i + \bar{\bar{O}}_i\right) - \min\left(\bar{\bar{I}}_i + \bar{\bar{O}}_i\right)$ (15)

3.4 ARAS method

ARAS describes an alternative under consideration, to the sum of the values of normalized and weighted criteria. and Turskis and Zavadskas (2010). The steps of procedure are explained below (Zavadska et al., 2010):

Step 1: Formulation of decision making matrix for the data having m alternatives (rows) and n criteria describing each alternative (columns). x_{ij} is value representing the performance value of the i alternative in terms of the j criterion and w_j be the criteria weights.

Step 2: The criteria, whose preferable values are minima, are normalized by first using Eq. (16) followed by Eq. (17) and the criteria, whose preferable values are maxima are normalized using Eq. (17).

$$xij = \frac{1}{xij} \tag{16}$$

$$xij = \frac{xij}{\sum_{i=0}^{m} xij} \tag{17}$$

Step 3: Normalized-weighted values of all the criteria are calculated as by $x'_{ij} = x_{ij} * w_j$ (18)

Step 4: The values of optimality functions of i alternative is S_i can be given by $S_i = \frac{xij}{\sum_{j=1}^{n} x'ij}$ (19)

The biggest value is the best, and the least one is the worst. The optimality function S_i has a direct and proportional relationship with x_{ij} and weights of the criteria and their relative influence on the final result.

Step 5: The degree of the alternative utility is determined by a comparision of the variant with the ideally best S_0. The utility degree U_i of an alternative A_i as: $U_i = S_i/S_o$. (20)

The utility values are in the interval [0,1] and can be used for the ranking of alternatives.

3.5 EVAMIX method

Evaluation of Mixed Data (EVAMIX) method was initially established by Voogd (1982; 1983), and later advocated by Martel and Matarazzo (2005). The novelty of EVAMIX method is that it deals with mixed (qualitative and quantitative) data. From a procedural point of view, EVAMIX method consists of the seven steps.

Step 1: First a set of objective is identified. Then, various attributes and alternatives are short listed for the given application. Using this information construct a data matrix of (mxn) size. Where n is number of alternatives and m is the number of relative attributes chosen for selection problem. Next step is to distinguish the ordinal and cardinal criteria out of decision matrix. Attributes are given the linguistic preference, can be converted into its corresponding crisp number as suggested by Chen and Hwang (1992).

Step 2: Normalizing the data set is done in the range of 0-1 using linear normalization procedure. The beneficial and non-beneficial attributes are weighted by different equations. For beneficial attributes, normalize the decision matrix using the following equation: The values will always maximum 1 and minimum 0.

- For beneficial attributes normalize the decision matrix using following equation:

$$r_{ij} = [x_{ij} - \min(x_{ij})]/[\max(x_{ij}) - \min(x_{ij})] \qquad (i = 1,2,...,m : j = 1,2,...,n) \tag{21}$$

- For non-beneficial attributes the above equation can be rewritten as:

$$r_{ij} = [\max(x_{ij}) - (x_{ij})]/[\max(x_{ij}) - \min(x_{ij})] \qquad (i = 1,2,...,m : j = 1,2,...,n) \tag{22}$$

Step 3: Calculate the evaluative differences of i^{th} alternative on each ordinal and cardinal criterion with respect to other alternatives. This step involves the calculation of differences in criteria values between different alternatives pair-wise. Pair-wise is done based on Analytic Hierarchy Process (AHP) Saaty (2000).It provides a way of breaking down the general data into a hierarchy of sub-data, which are easier to evaluate. These comparisons may be taken from actual measurements or from a fundamental scale which reflects the relative strength of preferences introduced by Fechner (1860) and further advocated by Turstone (1927).

Step 4: Compute the dominance scores of each alternative pair, (i, i') for all the ordinal and cardinal criteria using the following equations:

$$\alpha_{ii'} = \left[\sum_{j \in O} \left\{ W_j \operatorname{sgn}(r_{ij} - r_{i'j}) \right\}^c \right]^{1/C} \tag{23}$$

$$\gamma_{ii'} = \left[\sum_{j \in C} \left\{ W_j \operatorname{sgn}(r_{ij} - r_{i'j}) \right\}^c \right]^{1/C} \quad \text{where} \quad \operatorname{sgn}(r_{ij} - r_{i'j}) = \begin{cases} +1 & \text{if } r_{ij} > r_{i'j} \\ 0 & \text{if } r_{ij} = r_{i'j} \\ -1 & \text{if } r_{ij} < r_{i'j} \end{cases} \tag{24}$$

The symbol c denotes an arbitrary scaling parameter, for which any arbitrary positive odd number, like 1, 3, 5, … may be chosen, O and C are the sets of ordinal and cardinal criteria respectively, and $\alpha_{ii'}$ and $\gamma_{ii'}$ are the dominance scores for alternative pair, (i, i') with respect to ordinal and cardinal criteria respectively. In order to be consistence, the same value of scaling parameter c is used in (23) and (24). It is assumed that the value of c for qualitative evaluation $\alpha_{ii'}$ is taken equal to 1. Evidently, all standardized scores should have the same direction, i.e., a 'higher' score should imply a 'large' preference. It should be noted that the scores $\gamma_{ii'}$ of the quantitative criteria also have to represent 'the higher, the better'.

Step 5: Since $\alpha_{ii'}$ and $\gamma_{ii'}$ will have different measurement units, standardization into the same unit is necessary. The standardized dominance scores can be written as: $\delta_{ii'} = h(\alpha_{ii'})$ and $d_{ii'} = h(\gamma_{ii'})$

Where h represents a standardization function. The standardized dominance scores are obtained using additive interval technique. The standardized ordinal score $\delta_{ii'}$ and cardinal dominance score $d_{ii'}$ for the alternative pair, (i, i') using additive interval technique is calculated by following equations:

Standardized ordinal dominance score $$\delta_{ii'} = \left(\frac{\alpha_{ii'} - \alpha^{-}}{\alpha^{+} - \alpha^{-}}\right) \tag{25}$$

Where α^{+} (α^{-}) is the highest (lowest) ordinal dominance score for the alternative pair, (i, i').

Standardized cardinal dominance score $$d_{ii'} = \left(\frac{\gamma_{ii'} - \gamma^{-}}{\gamma^{+} - \gamma^{-}}\right) \tag{26}$$

Where γ^{+} (γ^{-}) is the highest (lowest) cardinal dominance score for the alternative pair, (i, i').

Step 6: Let us assume that weights W_j have quantitative properties. The overall dominance measure $D_{ii'}$ for each pair of alternatives (i, i') is:

$$D_{ii'} = w_O \delta_{ii'} + w_C d_{ii'} \tag{27}$$

Where W_j is the sum of the weights for the ordinal criteria ($W_o = \sum_{j \in o} W_j$) and W_c is the sum of the weights for the cardinal criteria ($W_c = \sum_{j \in c} W_j$).This overall dominance score reflects the degree to which alternative a_i dominates alternative $a_{i'}$ for the given set of attribute and the weights.

Step 7: Calculate the appraisal score.

The appraisal score for i^{th} alternative (S_i) is computed which gives the final preference of the candidate alternatives. Higher the appraisal score better is the performance of the alternatives. The best alternative is one which has the highest value of the appraisal score.

Appraisal score $$(S_i) = \sum_{i'} \left(\frac{D_{i'i}}{D_{ii'}}\right)^{-1} \tag{28}$$

4. Computations of proposed decision making methods

4.1 Extended TODIM computations

The extended TODIM method is applied for best material selection. By using Eq. (1) format of crisp criteria values are transformed into the format of random variables with cumulative distribution functions. To save the space, we only give results of calculations for entire computations. By using Eq. (2)-(3) forteen gain and loss matrices are constructed. These forteen matrices are normalized using Eq. (4)-(5) and based on Eq. (6)-(7), the dominance degree for the gain and loss is calculated. The aggregated dominance degree matrix is constructed using Eq. (8). By using Eq. (9) the overall dominance degree is calculated and finally using Eq. (10) the overall values for each alternative is determined. Table 2 shows the final calculations and ranking of the materials.

Table 2. Computational details and ranking using Extended TODIM method.

Materials	Values of overall dominance degree matrix Δ					Overall value $\xi(A_i)$	Rank
J4	0	-4.1853	-6.1888	-2.0405	-2.0662	0.8688	2
JSLAUS	-6.2996	0	-6.1107	-4.4562	-3.2395	0.7674	3
204Cu	-3.4480	-0.3161	0	-2.7015	-0.7333	1	1
409 M	-16.9232	-15.8252	-18.2753	0	-11.6548	0	5
304	-12.3748	-9.8102	-13.1057	-4.6547	0	0.4098	4

4.2 OCRA computations

Using Eq. (11), the aggregate performance of the alternative with respect to other non-beneficial attribute is calculated. Then based on these values, the linear preference rating for the non-beneficial attribute is computed using Eq. (12). Applying Eq. (13), the aggregate performances for the alternatives on all the beneficial attributes are then determined and subsequently, the linear preference rating for the beneficial attribute is calculated using Eq. (14). Finally, using Eq. (15), the overall preference rating for each of the candidate alternatives is derived. The computation details of this method are shown in Table 3.

Table 3. Computational details and ranking using OCRA method..

Materials	$\bar{I}_i$	$\bar{\bar{I}}_i$	$\bar{O}_i$	$\bar{\bar{O}}_i$	P_i	Rank
J4	6.4707	6.3368	0.0700	0.0667	6.4035	3
JSLAUS	2.3469	2.2125	0.0814	0.0781	2.2907	4
204Cu	9.1913	9.0573	0.0794	0.0761	9.1334	2
409 M	0.1339	0	0.0033	0	0	5
304	10.2970	10.163	0.0192	0.0159	10.1789	1

4.3 ARAS computations

After formulation of decision making matrix, the normalized-weighted values of all the criteria are calculated. The criteria, whose preferable values are minima, are normalized by applilying two stage procedure i.e., Eqs. (16)-(17). The criteria, whose preferable values are maxima, are normalized using Eq. (17). The normalized-weighted values of all the criteria are calculated by using Eq. (18). Finally using Eq. (19) the values of optimality function (S_i) are calculated. The degree of utility (U_i) of alternatives using Eq. (20). The ranks and necessary calculations are tabulated in Table 4.

Table 4. Computational details and ranking using ARAS method.

Materials	% OE	C	CR	WR	YS	UTS	H	Si	Ui	Rank
J4	0.0074	0.0803	0.0118	0.0377	0.0132	0.0059	0.0202	0.1765	0.4803	3
JSLAUS	0.0061	0.0428	0.0061	0.0394	0.0145	0.0064	0.0200	0.1353	0.3684	4
204Cu	0.0064	0.0750	0.0378	0.0415	0.0143	0.0064	0.0198	0.2012	0.5476	2
409 M	0.0111	0.0489	0.0047	0.0259	0.0093	0.0037	0.0161	0.1197	0.3257	5
304	0.0059	0.1011	0.1889	0.0401	0.0088	0.0049	0.0177	0.3674	1	1

4.4 EVAMIX *computations*

A set of materials listed in Table 1 are distinguished based on Ordinal and cardinal nature of criteria values. Normalization is done using Eq. (21) and (22) for beneficial and non-beneficial separately. The dominance scores of each alternative pair, (i,i') for all the ordinal and cardinal criteria using Eqs. (23)-(24). By using Eqs. (25)-(26) the standardized ordinal and cardinal dominance scores are computed. The overall dominance measure $D_{ii'}$ for each pair of alternatives (i,i') is computed using Eq. (27) and finally using Eq. (28), the appraisal score for alternative is computed using additive interval technique. Higher the appraisal score better is the performance of the alternative material. Table 5 gives the appraisal score and ranking of alternative materials for pipe in sugar industry.

Table 5. Computational details and ranking using ARAS method.

Materials	Appraisal score (S_i) using additive interval method	Rank
J4	0.1789	3
JSLAUS	0.0684	4
204Cu	0.3844	2
409 M	0.0624	5
304	0.8335	1

5. Results and discussions

The comparative results show that application of Extended TODIM, OCRA, ARAS and EVAMIX providing valuable assistance for material selection using decision making methods in varieties of problems. The results of the proposed methodologies are tabulated in Table 6. Extended TODIM and PROMTHEE result into a good selection when the cost is an influencing criterion for the selection. The results obtained using other methods suggest 304 is the best suitable material for pipes in sugar industry.

Table 6. Comparison of results obtained using proposed methods and previous methods.

Materials	Extended TODIM	OCRA	ARAS	EVAMIX	TOPSIS	VIKOR	ELECTRE	PROMTHEE
J4	2	3	3	3	3	3	3	2
JSLAUS	3	4	4	4	4	4	4	4
204Cu	1	2	2	2	2	2	2	1
409 M	5	5	5	5	5	5	5	5
304	4	1	1	1	1	1	1	3

6. Conclusions

The material alternative 304 (nickel containing austenitic 300 series) has obtained first position in all proposed methods except Extended TODIM for the pipes in sugar industry. Stainless steels have an excellent track record and are the materials of choice for numerous applications in the industry having heavy rate or corrosion and abrasion or wear. Stainless steels are is tough, ductile, having good strength and ease of fabrication. It is readily available worldwide in wide in variety of product forms. In addition, stainless steels are easily maintained to give an attractive and hygienic application. The recyclability of stainless steel supports the long term sustainability concept and goals. The proper material selection plays a vital role for reducing the corrosion and abrasion (wear) of the pipes in acidic nature of the sugar cane juice. The present paper has disclosed the intelligent and logical MCDM methods Extended TODIM, OCRA, ARAS and EVAMIX to evaluate suitable material for pipes. The comparison is done with the result obtained by the previous researchers, which is found to be the same. The methods proposed are more specific and efficient compared with the previous methods. Thus, in future these methods can be used for the selection of other parts or processes in the sugar industry.

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